Bio-inspired Mechanisms for Artificial Self-organised Systems

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Keywords: self-organization, stigmergy, reinforcement, cooperation

Received: [Enter date]

Self-organization is a growing interdisciplinary field of research about a phenomenon that can be observed in the Universe, in Nature and in social contexts. Research on self-organization tries to describe and explain forms, complex patterns and behaviours that arise from a collection of entities without an external organizer. As researchers in artificial systems, our aim is not to mimic self-organizing phenomena arising in Nature, but to understand and to control underlying mechanisms allowing desired emergence of forms, complex patterns and behaviours. Rather than attempting to eliminate such self-organization in artificial systems, we think that this might be deliberately harnessed in order to reach desirable global properties. In this paper we analyze three forms of self-organization: stigmergy, reinforcement mechanisms and cooperation. The amplification phenomena founded in stigmergic process or in reinforcement process are different forms of positive feedbacks that play a major role in building group activity or social organization. Cooperation is a functional form for self-organization because of its ability to guide local behaviours in order to obtain a relevant collective one. For each forms of self-organisation, we present a case study to show how we transposed it to some artificial systems and then analyse the strengths and weaknesses of such an approach.

1 Introduction

Self-Organization refers to a broad range of pattern-formation processes in both physical and biological systems, such as sand grains assembling into rippled dunes, chemical reactants forming swirling spirals, cells making up highly structured tissues, and fish joining together in schools. Concepts and mechanisms relatives to self-organization in biological systems have been largely defined and explained in [1]: basic modes of nonlinear interaction among components as well as information acquisition and process. In most self-organised systems in biology nonlinear interactions involve amplification or cooperation. Complex behaviours may emerge even though the system is composed of similar units that follow local rules and without intervention from external guiding influences.

Computer science is interested in understanding the underlying principles of self-organization because -like in nature- the rules specifying interactions among many artificial system's components are executed using only local information, without reference to the global pattern, which is not easily accessible or possible to be found. For more developments on self-organization and emergence, see the overview in [17].

The following three parts concern different mechanisms of self-organization in either ethology or cellular biology: stigmergy, reinforcement and cooperation. In each part, after description of the general principles of the mechanism, we develop the understanding of a particular instance, especially for the quite new instances of stigmergy and reinforcement mechanisms that come from agent-based simulation models we undertook with biologists.

Then we present a case study to show how we transposed it to some artificial systems.

More indeed, in the first part we analyse the stigmergy mechanism allowing indirect task coordination and regulation in insects societies or social spiders. This principle is replicated with some changes to be used in some artificial applications like region detection.

In the second part we present a reinforcement mechanism together with direct interactions studied in ethology and how it leads to specialization in groups of animals. The transposition of these mechanisms concerns dynamic task allocation in a network.

In the third part we study a cooperation mechanism observed between cells as well as in animal societies. This phenomenon is applied in artificial neural networks in order to produce plasticity and adaptation

In the last part we discuss about strengths and weaknesses of self-organizing principles in order to engineer artificial systems.

2 Self-organization Patterns from Stigmergy Mechanisms

2.1 Stigmergy Mechanisms in Biology

Stigmergy has been defined by the biologist Grassé [2] to refer to the mechanism by which the termites coordinate their nest building activities. In stigmergic labour it is the product of work previously accomplished, rather than direct communication among nest mates, that induces the insects to perform additional labour [3]. It explained how individual builders could act independently on a structure without direct interactions or sophisticated communications. The state of the building is the stimulus, its response is the construction activity.

So a stigmergic process is a sequence of indirect stimulus/responses behaviours and contributes to the coordination between insects through the environment. Another illustration of how stimergy and self-organization can be combined into more subtle adaptive behaviours is recruitment in social insects. Self-organised trail laying by individual ants is a way of modifying the environment to communicate with nest mates that follow such trails. It appears that task performance by some workers decreases the need for more task performance: for instance, nest cleaning by some workers reduces the need for nest cleaning [4], [5]. Therefore, nest mates communicate to other nest mates by modifying the environment (cleaning the nest), and nest mates respond to the modified environment (by not engaging in nest cleaning); that is stigmergy. Division of labor is another paradigmatic phenomenon of stigmergy. But by far more crucial, is how ants form piles of items such as dead bodies (corpses), larvae, or grains of sand. There again, stigmergy is at work: ants deposit items at initially random locations. When other ants perceive deposited items, they are stimulated to deposit items next to them, being this type of symmetry clustering organization and brood sorting a type of self-organization and adaptive behaviour. There are other types of examples (e.g. prey collectively transport), yet stigmergy is also present: ants change the perceived environment of other ants (their cognitive map, according to Chialvo [6]), and in every example, the environment serves as a medium of communication. Finally, stigmergy is often associated with flexibility: when the environment changes because of an external perturbation, the insects respond appropriately to that perturbation, as if it were a modification of the environment caused by the colony's activities. In other words, the colony can collectively respond to the perturbation with individuals exhibiting the same behaviour.

What all these examples have in common is that they show how stigmergy can easily be made operational because of the simplicity of the behaviours involved.

2.2 Stigmergy Mechanism Under-standing

Dorigo [5] replicated stigmergic principle from ants colony, including the pheromone trails, to derive algorithms applied either to static or dynamic combinatorial optimization problems with applications on many problems like the traveling salesman problem. The brood sorting behaviour can be reproduced with robots, for example, to achieve collective sort [7]. We replicate another kind of stigmergic mechanism to perform region detection. We analyse the stigmergy process involved during the building of web in a species of social spiders through an agent-based model. This simulation shows that the mechanism that underlies the movement of spiders can be expressed as a stigmergic one where silk and silk attraction play the major role.

The web weaving activity needs two behavioural items: movement and silk fixing. Items are independent i.e., a spider-agent (SA) can make these two action types at the same time: to move to a close stake and to fix a silk dragline. Furthermore, items are fired stochastically according to a constant or contextual probability. When fixed, the dragline provides a new path (the shortest one) between the current stake and the last on which silk was fixed (whatever the spider moves were). The probability to fix the silk is constant over time. When a SA moves, it can be from the current stake to an adjacent one (the 8 accessible neighbours). Since silk draglines are fixed between stakes, they offer new directions of movement. When facing such a situation, the SA has to choose whether to follow a dragline or to move to an adjacent stake. The probability for a SA to move to a given stake depends on the type of access. In the neighborhood, the probability is constant.

When following a silk dragline, the probability is proportional to the number of silk draglines and to the silk attraction. This mechanism that underlies the movement can be expressed as a stigmergic process. Studies [18] demonstrated the key role of the silk attraction: when too low, no web is built and all available space is used; when too strong, SA were trapped in their own silk and no collective weaving occurred; when well chosen, we showed that the web size is related to the attraction: the more the attraction is, the smaller the covered surface is.

The behaviour of the colony of spider-agents can be interpreted as much as:

- A stigmergy pattern a collective mechanism for space exploration which is characterized by limited perception and indirect interaction, the environment (the web woven by spiders) being the medium of interaction,
- as a self-organised pattern with some regulation performed without explicit coordination, the size of the explored space (the size of the web) being related to the silk attraction factor.

2.3 Region Detection by Stigmergy

This stigmergy process has been transposed to region detection. The problem is to extract a region from an image. A region must be a connected set of pixels with homogeneous radiometric characteristics. In our case, all the pixels of a region should have the same grey level, more or less a given tolerance. From a given picture, our model produces an intermediate structure constituted by the woven collective web, interpreted later to deduce region by considering the pixels on which the web is fixed. It requires an exploration of a space that has to be restricted to a subset of its elements (the pixels of the region).

A grey level image is the environment in which agents will evolve; stakes correspond to pixels and the height to their grey level. The behavioural items of agents are similar to SA. The movement remains unchanged and silk fixing now depends on the context and, thus, is related to the grey level of the region to detect. The interaction principle is based on stigmergy. To avoid different regions of the same grey level being woven on a unique web a third behavioural item was added to make an agent probabilistically return back to the web [19]. All agents have the same features determined by four parameters. Two parameters govern the movements of the agents and thus the exploration process. The two last ones are related to the selection of pixels, thus determining the relevance of the extracted region. Because the process is based on the stigmergy ensured by the silk draglines laid down in the environment, selection and movement are tied. But we could initially specify the influence of silk attraction factor as shown in figure 1: when it is high (the left picture) the five agents construct five different webs and do not explore the entire region. When it is low (the right picture) the region covered is bigger and corresponds to a collective web. Thus, when well chosen the parameters for stigmergic process allow decentralised coordination.

Fig.1. Influence of silk-attraction factor on webs for detection region

3 Self-Organization from Reinforcement Mechanisms

3.1 Reinforcement Mechanisms in Biology

Reinforcement has been discussed as a mechanism that shapes the differentiation between specialists and the remaining work force. The concept of reinforcement proposes that the impact of a single worker on stimulus intensity increases with experience. This can be achieved in one of two ways: first, the efficiency of a worker may increase with experience, e.g. because individuals learn to perform a task. Second, response threshold for task associated stimuli may decrease with experience in performing the task [8]. Learning and increase in task efficiency have often been considered as the main reason for the efficiency of division of labor [9], [10]. Then, reinforcement may play an important role in specializations [11].

Reinforcement learning is a synonym of learning by interaction. During learning, the adaptive system tries some actions (i.e., output values) on its environment, then, it is reinforced by receiving a scalar evaluation (the reward) of its actions. The reinforcement learning algorithms selectively retain the outputs that maximize the received reward over time.

Reinforcement mechanisms like increase in task efficiency assiociated with direct interactions in biology conducts to social organization, specifically dominances hierarchies [12]. For example, dominances hierarchies are obtained by simple model based on positive feedback. Two individuals enter in a contest. An individual that wins or loses the contest is more likely to win or lose subsequent contests. The reinforcement mechanism amplifies small initial differences between individuals.

3.2 Reinforcement Mechanism Understanding

The problem of reinforcement learning is knowing what to reinforce. Motivation cannot rely on a blind mechanism that strengthens or weakens connections based on their temporal proximity to pain or pleasure stimuli. While temporal difference reinforcement may work well enough in small systems, it becomes prohibitive in large systems.

The second reinforcement mechanism is relevant when we want to realize a distributed collective task implying a lot of agents. As an example, an elaborate self-organized phenomenon is observed in rats' groups in the diving-for-food situation. This situation is a complex social task in which, for a group of six rats, the food accessibility decreases by progressive immersion of its only path. This experimental schedule leads to the emergence of a specialization in the group of rats, in two profiles: supplier and non-carrier rat. The non-carrier animals never dive, but get food only by stealing it from the suppliers after fight. The supplier rats dive, bring the food back to the cage and cannot defend the food they carried.

An agent based simulation shows that this social differentiation is possible from a set of interacting individuals without any social cognition. It implements two reinforcement mechanisms: when the action of diving is performed the anxiety of the rat is reduced according adaptive response thresholds models [8]. Whether the action of fighting is successful or not, the strength of the winner is reinforced whereas the strength of the looser is decreased. Alterations of strength are computed according to dominance formula presented in [12]. This specialization is stable, robust and presents adaptive properties like adaptation to the number of agents or adaptation to external conditions [13]. For example, the ratio between carrier agents and supplier agents' number evolves according to the energetic supply coefficient of a pellet.

3.3 Task Allocation in a Computer Network by Reinforcement Mechanism

The general framework to transpose these mechanisms consists in a dynamic task allocation problem among machines, connected together in a network. Initially the tasks are available on a central server. The machines can acquire the data by accessing directly the server or by 'attacking' each other. As some policies are put on the server in order to avoid crash, some agents can easily access the server while other not. The aim of the self organized process is to reduce the exploitation of the network between the machines and the server by means of specialization among machines. It corresponds to dynamically (and efficiently) allocate tasks on an unknown set of machines by making some of them accessing directly the server (because it is easier for them) while others acquire data indirectly (as shown in figure 2).

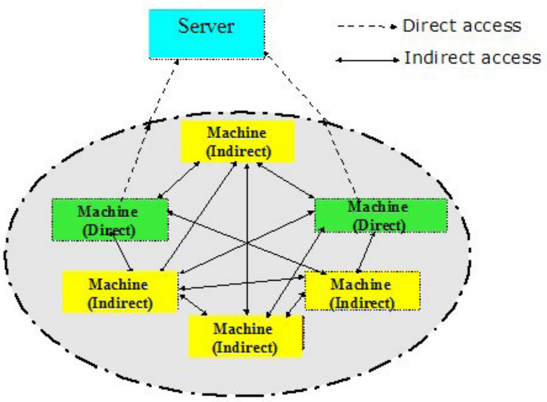

Figure 2. Expected organization for task allocation problem in network

We developed a prototype at applicative layer of the network that assumes existing communication architecture and that only deals with the data processing including execution and redirection. The first tests have been performed with a simulator including the server, the machines and the network. We got some encouraging results like specialization appearance and some improvements in processing time. These results are today obtained with only specific instances of the problem and with hand tuned parameters.

4 Functional Self-Organization from Cooperative Mechanisms

4.1 Cooperative Mechanisms in Biology

We analyse cooperation in complex biological systems trough four main kinds of mechanisms: parallelism, coordination, specialization and recruitment. Those mechanisms are presented according to the interaction complexity between parts of the biological system.

- Parallelism defines the more basic level of cooperation. When different elements of the system are independent in their activities, but share a common goal, they make up a parallel system. Polistes Wasps' nest construction [20] is a good example of parallel activity: wasp workers are interchangeable; they share a same goal that is building the biggest nets as quickly as possible. Efficiency of such a system depends mainly on the number of constitutive elements.
- Coordination is observable when at least two elements of the biological system have to act together or simultaneously in order to perform a particular task impossible to achieve by an alone agent. A demonstrative experience is provided when ants have to act collectively to take a straw off the entrance of their nest. Theoretically, at least two ants are required: when the first ant has lifted up the straw of a few millimetres, the second ant catch the straw lower than the first ant and lift it up on her turn. Because of the lack of intentionality in ants, this example can be discussed as a singularity of parallel system. So, another kind of coordination appears when army ants make bridges with they bodies to smooth the trail between sources of food and their nest.
- Specialization increases the heterogeneity of the biological system, addressing a particular task or function to some elements of this system. In fact system's activity is improved thanks to some elements that either become more efficient in a subset of activities that was already performed or become able to perform new kinds of tasks. The best example in cellular streams [21] is the specialisation of cells which at the simplest level favours a branch of their metabolic activity to high rate to store and produce metabolites for other cells or for the whole organism. At a more complex level, cells can specialize in modifying their structure and develop particular abilities like production of antibodies in immunity cells, gas transportation in blood red corpuscles, chemical energy storage in liver cells, or production and propagation of spikes in neurons.

- Recruitment and mass effect occurring in foraging or in colony aggregation, present a real interest when collective behaviours improve single ones and beyond trigger events that a few elements wouldn't have produced. This part of cooperative mechanisms clearly includes reinforcement mechanisms discussed in part 3.1. Many examples in nature illustrate mass effect like temperature regulation in penguin colonies, improvement of predator detection in sheep flock, or reaching locally a threshold concentration in trophic factor during embryogenesis that will trigger specialization of cells exposed to this threshold. Regulation is the inherent counterpart of recruitment, and prevents the biological system from being trapped in a single activity before its exhaustion.

4.2 Cooperation Mechanism Understanding

Self-organization concerns always several entities that act, from an external point of view, as a coherent collective. Beyond self-organization, cooperative self-organization constrains more precisely the behaviour of these entities in order to make their interaction reach most of the time, a state of cooperation. From the point of view of the entity the three phases of her functioning are concerned by cooperation:

- At the perception phase the signal received by an entity from its environment or from a second entity (social environment) must not be misunderstood or ambiguous .
- At the processing phase, the information contained in the signal must not be unproductiveness or inability.
- At the action phase, the decision of the entity (transformation of the world or even message sending) must not be useless, or implying some concurrency or conflict in its environment.

This is the basic cooperation principle inspiring the AMAS theory [14], which will be used, in many applications such as the following adaptive neural network.

4.3 Cooperative Artificial Neural Network

Biological neural structures may be considered as the combined result of self-organizing cellular activities and of the following of many strong planned processes. Such a system is the result of the permanent reorganization of its parts upon among others, the pressure of its environment.

The concept of cooperative neuro-agent (CNA) can be detailed in three functional subsets that justify the neuro-agent term [15]. CNAs have the usual transfer function of an artificial neuron, have also a vegetative behaviour and have moreover a set of cooperative social behaviours according to the laws of the AMAS theory. The role of vegetative and social behaviours accounts mainly for balancing the lack of an initial topology in the network.

Cooperative behaviour when addressing to CNAs, means that CNAs help each other to find not only their right place in the network but also their right function in the network. Back propagation is cooperative as it helps CNAs to find their function but is not sufficient to position them in the network. So we can distinguish two other sets of cooperative behaviours. The first includes pro-cooperation, for example when a CNA informs one of its neighbours that it is searching accountancies, with the rest of its neighborhood (including virtual links). The last set regroups the behaviours appearing to resolve some particular potential and well defined troubles: the non cooperative situations.

CNA Coordination. The objective of a CNA is to be useful to the others by having a coherent activity and supplying them with relevant information. So, learning consists in reinforcing weights according to correlated temporal activities of inputs. A CNA estimates the rightness of its activation by interpreting messages from its outputs. Following the mean error, a CNA adjusts the weights of the concerned inputs. As in a back propagation mechanism, a CNA informs in turn its inputs of the error it has detected.

That means that a CNA modifies its functioning to fulfil other CNAs it is working with. So at a given time the behaviour of a CNA is the result of its code expression under the regulation of its local environment.

CNA Specialization. A CNA realizes a positive integration of the information carried through incoming links, and then this weighted sum is transformed using a non-linear transfer function into a positive integer value. A CNA can also use an inhibitory input that nullifies the transferred value.

When the coordination process adapts insufficiently its output, a CNA modifies its transfer function. Thus we can observe, at the collective level, clusters in which neuro-agents have a similar transfer function. Moreover, a CNA can be used as activator or inhibitor to others. Without any predefined role, some CNAs tend to be used preferably (but not exclusively) as inhibitors.

CNA Recruitment. If a CNA keeps on receiving error messages that it cannot satisfy, it triggers an adaptation process of the network structure. We call this process vegetative behaviour, as the CNA can determine by itself whether it has to proliferate or search for new inputs, or if finally it has to disappear in an apoptosis-like mechanism.

This vegetative behaviour grants the dynamics and the self-organization of the network. That is why the learning stage begins with a not connected network where only inputs and outputs of the future network are created. The mother CNA provides all the required instances, which are an exact copy of it. Nevertheless, the basic transfer function of the mother cell is adjusted in each individual CNA in order to find the best cooperative behaviour in accordance with its neighbourhood.

Emergent Collective Behaviour. A CNA network is initialized with only not connected CNAs located at the interfaces (input and output of the network). The behaviour of CNAs only depends on the local perception CNAs get about the system, and finally there is no imposed pattern which supervises the organization of the system. Based on local non-cooperative criteria of neuro-agents, the system adjusts its function by reorganizing its parts. So the learning of the system globally results from population growth and from neuro-agents adaptation (weight adjustments, transfer function regulation, search and disappearance of connections).

The simple test case of learning a XOR logical function illustrates perfectly the different aspects of cooperation in a neural network. The initial step requires two inputs and one output as shell of the future network; that means 3 CNAs. Obviously they are not sufficient for computing a XOR function, so they have to recruit at least a fourth CNA which will inhibit the output of the network when both inputs are activated. In the figure 3 we can distinguish a first period of proliferations that do not improve the global learning performance, but give the network with the ability (in terms of neural population) of realizing the right function. In a second period, each CNA specialises itself in an integrator and coordinates the information flow between them by adjusting weights until outputs of the network do not produce errors anymore. Useless CNAs are eliminated.

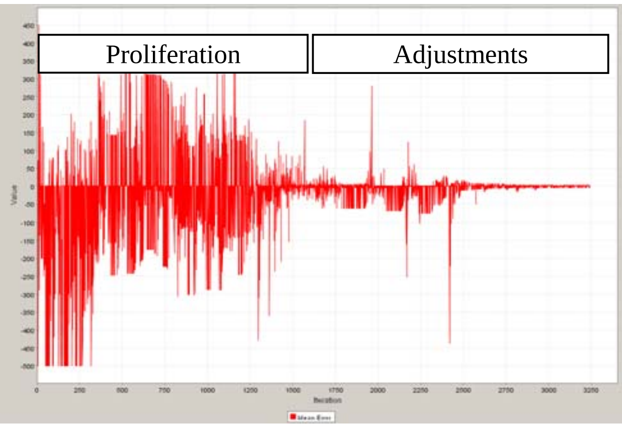

Figure 3 : Graph of the global error of a network learning a XOR function

5 Strenghts and Weaknesses of Self-organizing Mechanisms

5.1 Analysis of the Case Studies

The first experiments we undertook in region detection demonstrate the potential of the transposition of spiders-inspired self-organised mechanisms. As mentioned by Bonabeau [4], stigmergy is a promising first step to design groups of artificial agents which solve problems: replacing coordination (and possibly some hierarchy) through direct communications by indirect interactions is appealing if one wishes to design simple agents and reduce communication among agents. Flexibility to perturbation is priceless: it means that the agents can respond to a perturbation without being reprogrammed to deal with that particular instability.

However a major drawback has to be solved in order to produce a real application of detection region: parameters are until now empirically adjusted and we also have to determine initial conditions: the numbers of agents and their initial position. The right number of agents could be automatically adjusted by using for example a stimergic mechanism from adaptive recruitment behaviours in social insects.

Some results for dynamic task allocation in a network have been obtained by transposing the model of specialization in rats group. We show that apparition of some social pattern is possible from a set of interacting individuals without any social cognition and no direct communication. But these results can only be obtained by trial-error experiments in an iterative process since exact behaviour of these systems could only be known a posteriori . In order to understand influences of either the parameters or the combinations of parameters, differential analysis is required and a lot of experiments are carried out. One experiment must be proceed a lot of times in order to be statistically valid. So it is useful to store a full and detailed review of preceding experiments and often to analyse data from previous experiment with multiple other views.

Cooperative neuro-agent network is today evaluated on logical functions, but is also applied to model the migration of leatherback turtles. Even working rightly on these cases, tuning the cooperative local behaviour in each entity of a system was difficult in order to obtain good specialization, coordination and recruitment behaviours. The result is mainly a very generic approach for artificial neural networks and an efficient search solution in the global space problem avoiding experimentally local minima.

5.2 Tools for the Self-organization Process

Usual learning techniques (Q-learning, reinforcement learning, genetic algorithms...) try to find a solution by the way of an individual even its learning is improved by the relationships with others. On the opposite, all self-organizing systems -including ants algorithms or swarm particle algorithms- share the ability to solve a global problem at the collective level, where micro-level components discover only a small part of the solution. This is the case for the mechanisms showed in the paper:

1. Spiders work together to create a web corresponding to an image region individually without knowing what is the collective result.
2. Machine specialization in a network is obtained from local reinforcement mechanisms without any centralized control.
3. Adequate neural structures come from local cooperative behaviour without any learning strategy derived from the global function to obtain.

The main advantage for all these self-organizing problem solving approaches is the complexity reduction, because they are only concerned by specifying agent behaviour, even the solved problem is related to the collective complexity. We can exemplify that by expliciting the parameters used in the case studies:

1. In stigmergy mechanisms, the two behavioural items of an agent, movement and selection, are defined by four parameters where silk attraction factor plays a key role.
2. In reinforcement mechanisms the three behavioural items, diving, fighting and eating are triggered according to parameters characterizing the internal state of an agent. These are hunger, strength and anxiety. The reinforcement parameters concern strength and anxiety.
3. In cooperation mechanisms, the local actions are associated with each non cooperative action an agent may encounter. For a cooperative neuro-agent these actions are proliferation and apoptosis of a neuron, regulation (increasing or decreasing the weight of an input) between its current inputs or specialization (improving or not the sensibility of the inputs) of its own transfer function.

Self-organized systems are characterized mainly by non linear dynamics, by sensibility to initial conditions and parameter sensitivity. Thus the overall properties cannot be understood simply by examining separately the components. With agent-based modelling, a lot of work remains to precisely identify the link between the local parameters and the global results obtained. In order to obtain dynamic equilibrium due to unexpected changes in the environment and non linearities inside the system, all self-organizing agents must manage a given action and also its opposite one. This is the actual weaknesses of self-organizing mechanisms, because a lot of time must be spent by engineers in order to find from experimentations the right decision criteria firing all these actions.

6 Conclusion and Prospects

In this paper, three approaches of self-organization inspired from biological systems were analysed and case studies applying these mechanisms were presented. The bio-inspired mechanisms showed have the main descriptive criteria as defined in [22]. There is no external control and no internal entity centralize information or decision. The solution is built dynamically and consequently unpredictable, due to the set of interdependent individuals working in parallel and able to react relevantly to their reciprocal activities. These applications have also the anytime property, because they are able to give a more or less good solution according to the time given to the processes.

Even if these approaches are able to solve difficult problems, the study of such complex systems needs experiments to explore their behaviours as Zambonelli claims [16]. Thus, a very useful perspective for these mechanisms will be to define theories allowing automatic tuning of their parameters.

Self-organization mechanisms guide the behaviour of the local entities of a collective. Consequently these approaches allow a drastic reduction of the solution search space compared to global search algorithms. Though this is experimentally observed, a lack of demonstrations by formal proofs still remains today.

Working on self-organization implies the creation of disorders inside a collective in order to obtain later a more relevant response of the system faced with unexpected events. From an engineering point of view it could be interesting to propose global systems gauges able to link disorder and relevance behaviour at the system macro-level. Some tools are today available on MAS platforms as described on the AOSE overview [23]. They must be completed by new works on entropy measure in artificial systems in order to have a more relevant observables on their dynamics.

Acknowledgment

The authors wish to thank Aurélien Saint-Dizier for the implementation of the network simulator.

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